AN6383

Application note

Implementing electrochemical impedance spectroscopy with ST solutions

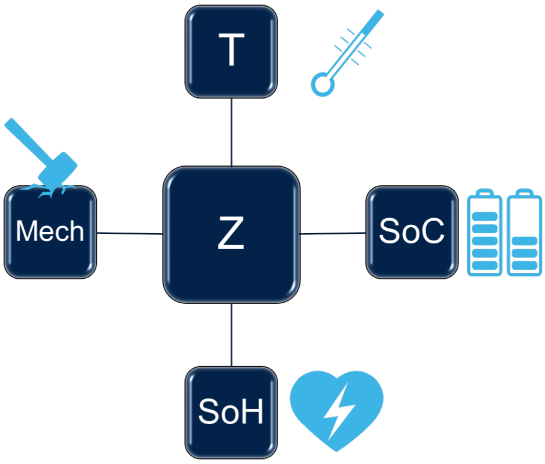
Introduction

The electrochemical impedance spectroscopy (EIS) methodology is a powerful and widely used non-invasive and non-destructive battery characterization technique based on estimating the impedance of batteries. It is useful to understand vital information about batteries and their constituent parts.

As batteries are now ubiquitous, the next innovation step is to leverage battery impedance measurements to enhance the user experience.

The EIS methodology applied to batteries enables the investigation of physical and chemical phenomena, using a non-invasive and non-destructive approach. This leads to the determination of essential information of batteries, such as the state of health (SoH), the precise estimation of cell internal temperature (increasing safety by preventing thermal runaway) and the state of charge (SoC).

Figure 1. **Battery performance parameter**



Batteries operate through electrochemical reactions that convert chemical energy into electrical energy during discharge and reverse this process during charging to restore their chemical composition for repeated use. Several factors can influence the conversion process within a battery, as shown in Figure 1, with the most important being:

- **Temperature**: it can affect the chemical reactions inside the battery, affecting its efficiency and lifespan.
- **State of charge**: the level of charge can influence the battery's ability to convert energy efficiently, with extreme states (fully charged or discharged) potentially causing degradation of the battery itself.
- **Age and cycle life**: over time and with repeated charging cycles, the materials within the battery can degrade, affecting its conversion efficiency.
- **Mechanical stress**: it can lead to increased heat and stress on the battery, potentially reducing its capacity and lifespan. Severe stress, such as penetration, can cause irreparable physical damage to the battery.

Battery performance is also tied to specific battery chemistry, which determines characteristics such as voltage, current capabilities, and charge and discharge rates. All these factors can significantly affect the performance and longevity of a rechargeable battery.

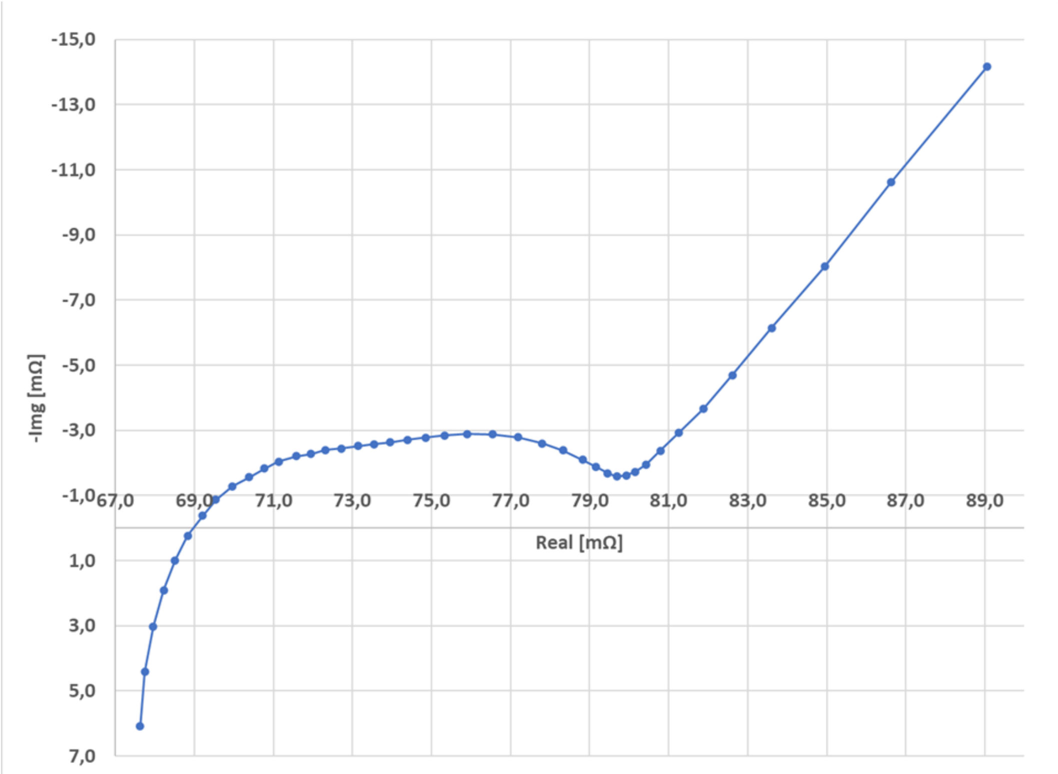
1 Electrochemical impedance spectroscopy

EIS is based on the perturbation of an electrochemical system in equilibrium or in steady state, via the application of a signal (AC voltage in potentiostatic mode or AC current in galvanostatic mode) over a wide range of frequencies. The response (current or voltage, respectively) of the system to the applied perturbation is then measured. Usually, a small alternating current perturbation signal (or voltage) is superimposed on the direct current bias that mimics the charge or discharge conditions of a cell.

Battery impedance is a frequency-dependent complex number, which is characterized by the ratio of voltage to current and the phase angle shift between them.

In the Nyquist plot, as shown in Figure 2, the imaginary part of the impedance is plotted versus the real part of the impedance. The Nyquist plot is commonly translated into a Cole-Cole diagram where the imaginary axis is inverted. By scrolling the plot from left to right, it ranges from high to low frequencies.

Figure 2. Nyquist diagram LG INR 18650 MJ1



2 ST EIS demonstrator setup

In Figure 3, Figure 4 and Figure 5, results obtained from a 32 Ah Li-ion prismatic cell (single cell analysis within the battery pack of five cells) are presented. The figure includes a Bode plot highlighting amplitude with respect to frequency, a Bode plot highlighting phase, and a Nyquist plot.

Figure 3. Bode amplitude

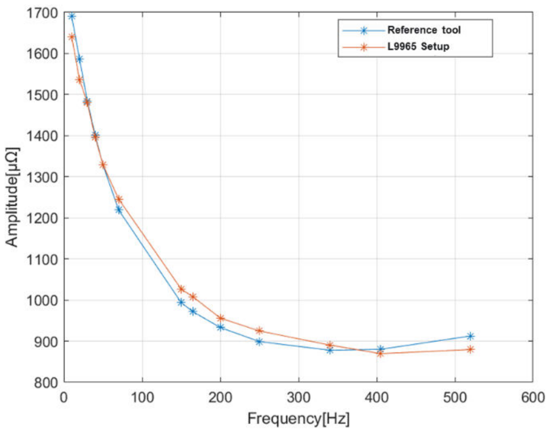


Figure 4. Bode phase

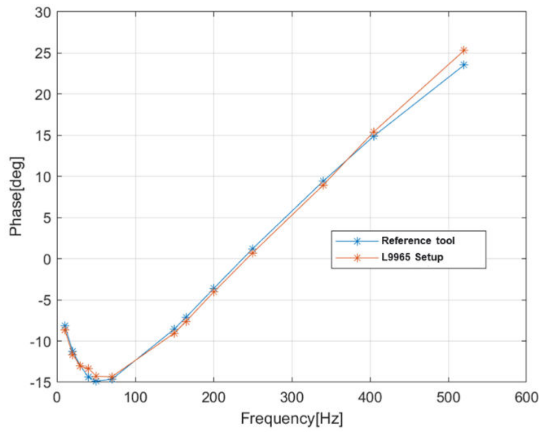
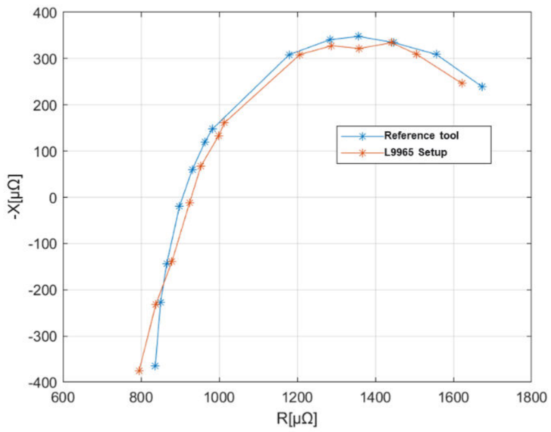
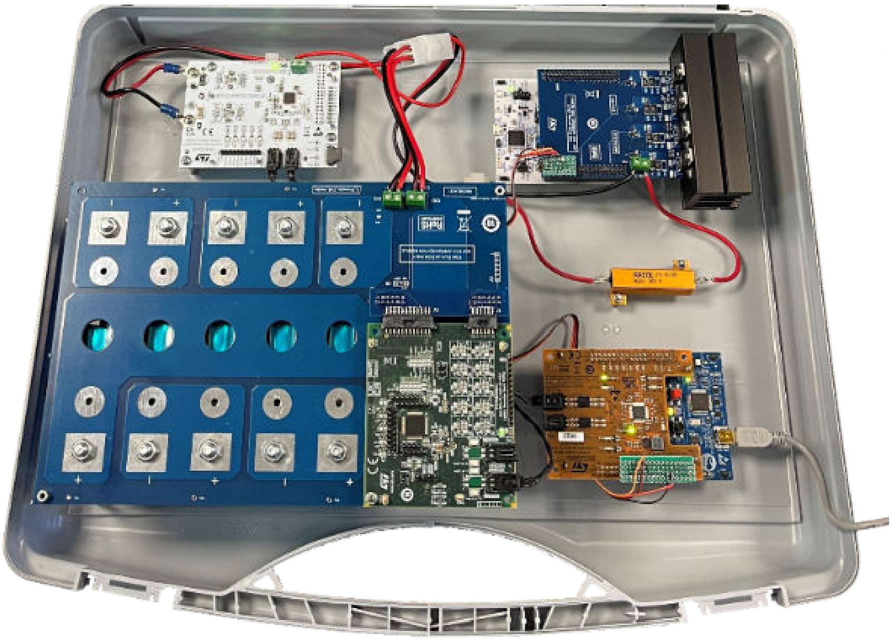


Figure 5. Nyquist plots



The curves are obtained with an EIS demonstrator setup and are compared to those obtained using a galvanostat measuring instrument, confirming a minimal error of about 24 μΩ for Bode amplitude, 0.6° for Bode phase and 29 μΩ for Nyquist (values for the single cell are shown in Figure 6).

Figure 6. **Example of EIS demonstrator setup**



Battery management ICs play an important role in ensuring the safety of users, while making sure they get the most out of their battery-powered devices. Battery management solutions require accurate voltage, current, and temperature measurements to ensure an appropriate safety level during battery operations.

The ST product portfolio offers a wide set of BMS products targeting different application segments: L9961 (with associated reference boards like STEVAL-L99615C), L9963E, and the latest L9965x family.

The proposed setup is based entirely on ST products, both hardware (HW) and software (SW). They have been built to show EIS performance of ST products, especially of the L9965x family. This setup is performing EIS on five series-connected cells.

3 Nyquist diagram: frequencies and features

The EIS complements and improves battery management system key tasks like SoC estimation, balancing, charging, and temperature monitoring. It also extends BMS with new functionalities, such as SoH and temperature estimation, increasing the level of safety, allowing thermal runaway prediction, and optimizing the life cycle and efficiency of the battery. Additionally, it potentially reduces costs.

Figure 7. Nyquist diagram with associated ECM (below) and electro-chemical information (green)

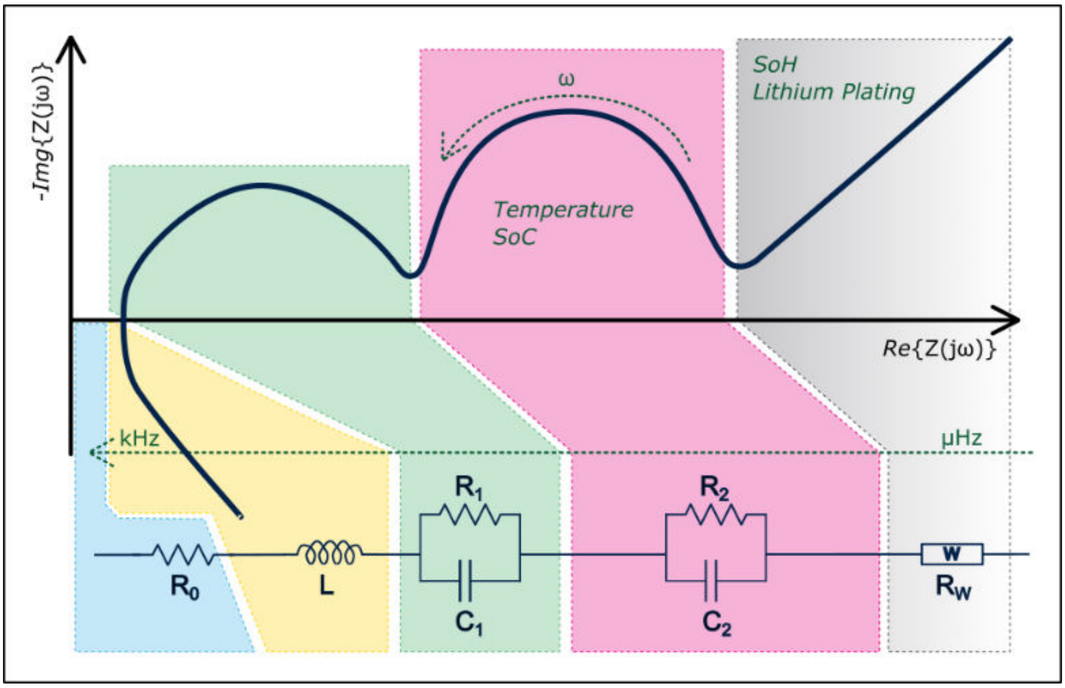


Figure 7 shows a theoretical Nyquist diagram, with each section corresponding to an electrical component of the battery's equivalent circuit model (ECM). The ECM translates key electrochemical phenomena (green text) into circuit elements, enabling quantitative analysis of the battery's internal processes.

Low-frequency impedance is correlated with the SoH of the battery and, particularly, with the degradation phenomena of lithium plating. Lithium plating occurs when metallic lithium deposits on the anode surface during charging, which can reduce battery capacity and increase safety risks, such as short circuits.

The two semicircles usually merge into one, and they correspond to charge transfer and double-layer capacitance processes at the electrode-electrolyte interfaces. These processes govern the kinetics of energy storage and release in the battery. Consequently, the diameter and shape of these semicircles are influenced by the battery's parameters.

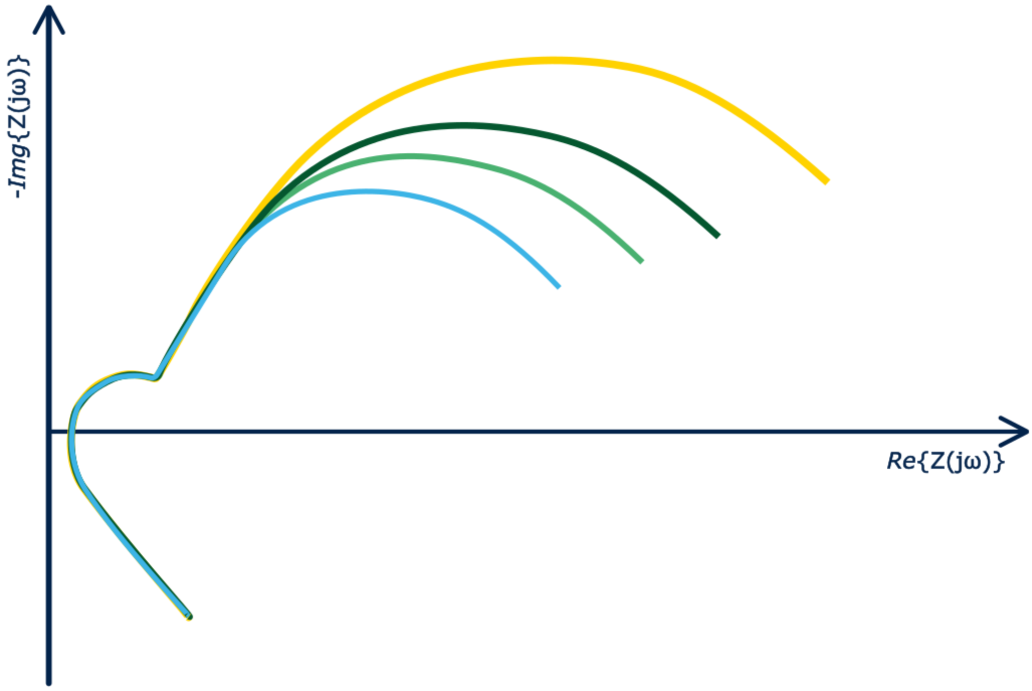
The diameter and shape of the semicircles in the Nyquist plot of the battery impedance can thus be used to precisely identify SoC, SoH, and temperature, as also reported in [2], [3], and [4]. Identifying features of the semicircle, such as its diameter or the peak (closer to the circle radius), is critical.

Figure 8 shows with different colors how the Nyquist diagram changes according to battery SoH from new (blue) to aged (yellow) batteries. A new battery could have a diagram similar to the light blue one. Aging due to charge/discharge or stress on the battery affects its diagram shape, making it shift to the light green one, then to the dark green one, and finally toward the yellow one after a long usage. Therefore, the peak of the second arc can be correlated with battery SoH.

A similar consideration holds for SoC. The application use case drives how to handle and correctly process measurements.

Figure 8. Different SoH: newest (1) to oldest battery (4)

1. *Light blue.*
2. *Light green.*
3. *Dark green.*
4. *Yellow.*



Another critical feature in the Nyquist plot is the point where the impedance curve crosses the real axis, that is, where the imaginary part changes from negative to positive. This interception is correlated to the battery's internal temperature, as temperature variations affect the electrolyte conductivity and charge transfer resistance. Monitoring this crossing point allows for non-invasive estimation of the cell's thermal state, which is crucial for battery management systems aiming to improve performance and ensure safety.

4 Nyquist plot feature extraction: peak detection

The frequency range chosen for the impedance measurement is related to the batteries used. Looking at the Nyquist diagram in Figure 7, the measurement loses importance for values of imaginary impedance below zero, as well as above the so-called Warburg impedance. In general, the higher the capacity, the lower the crossing frequency at the point where the imaginary impedance is zero. Conversely, with smaller batteries in parallel, the frequency of interest increases.

It is extremely important that real-time implementation needs to be fast and energy-efficient. Addressing specific features of the diagram using a fast algorithm helps in working at a temperature and state of charge (SoC) that can be considered constant.

In order to address this, it is preferable to work on a limited set of impedance measurements to avoid the following drawbacks of a full Nyquist diagram:

- Taking too long to gather all the information, as excitation signals may theoretically range from mHz to kHz.
- Undesired battery excitation, particularly at lower frequencies, which stresses the battery and may cause heating.
- Heating, which alters battery physics, thereby affecting EIS measurements.

The following approaches reduce time and energy used to excite the battery cells, thus reducing losses in EIS evaluation systems, allowing online operation, reducing power consumption, minimizing battery stress, and lowering computational time.

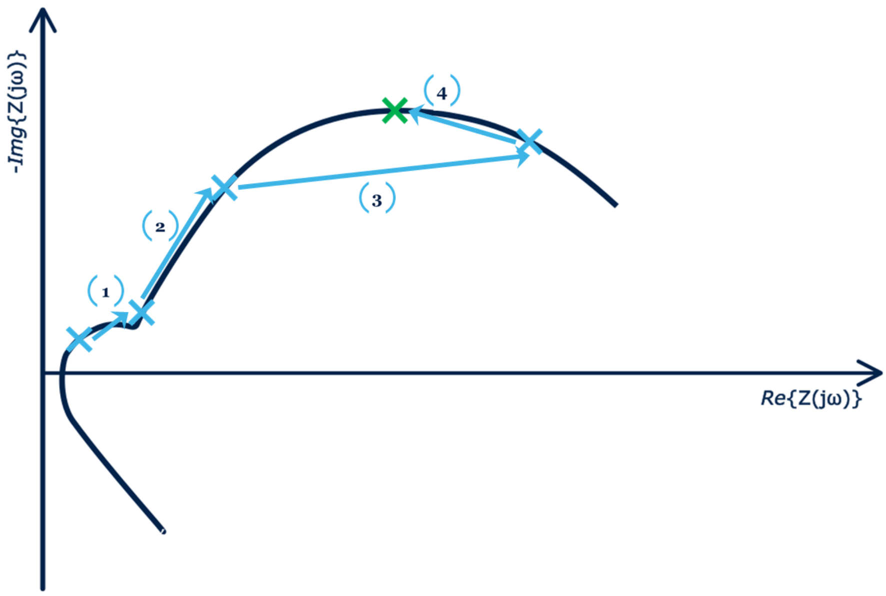
The peak position of the second arc of the Nyquist diagram (in the same battery charge condition) could be used to estimate the SoX function.

4.1 Peak search

A possible implementation of peak detection could be to perform different measurements at different frequencies, looking for the peak of the impedance. Like any other optimization problem, a gradient descendant method can be used to find the peak. This procedure must find the minimum impedance.

It is worth noting that any other optimization algorithm, rather than the simple GD method, can be used as well.

Figure 9. **Algorithm steps**



As reported in Figure 9, the following steps can be performed:

1. Peak search starts at higher frequencies. This way, the algorithm starts from higher impedance values.
2. The gradient descent (GD) algorithm can be used to find the peak associated with the minimum value of the impedance (steps from 1 to 4 in the picture).

It is worth noting that this approach reduces the number of measurements, while also reducing the time and energy used to excite the battery cell. A lower limit in the frequency range should be considered to avoid the Warburg region where, unfortunately, the impedance value always decreases compared to the frequency.

4.2 Circle fitting

Another possible implementation of peak detection could be to perform different measurements at different frequencies, trying to extract the parameters of the circle composing the second arc of the Nyquist diagram. Basic geometrical consideration implies that only three points are needed to identify a circle parameter. The following holds:

- Given the well-known circle equation:

$$x^2 + y^2 + 2ax + 2by + c = 0$$

- Given the three measurement points in cartesian representation (x_n, y_n), where x is the real part of the complex impedance and y is the imaginary part, circle parameters a, b, c can be evaluated by solving:

$$\begin{bmatrix} 2x_1 & 2y_1 & 1 \\ 2x_2 & 2y_2 & 1 \\ 2x_3 & 2y_3 & 1 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} -x_1^2 - y_1^2 \\ -x_2^2 - y_2^2 \\ -x_3^2 - y_3^2 \end{bmatrix}$$

- And thus:

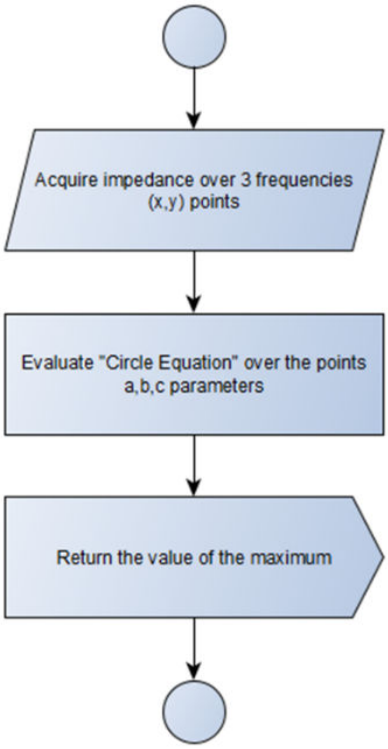
$$\begin{cases} x_M = -a \\ y_M = -b + \sqrt{a^2 + b^2 - c} \end{cases}$$

Where x_M and y_M are the cartesian coordinates of the impedance peak in the Nyquist diagram. These can be used as input for SoX estimation.

Figure 10 reports the algorithms steps:

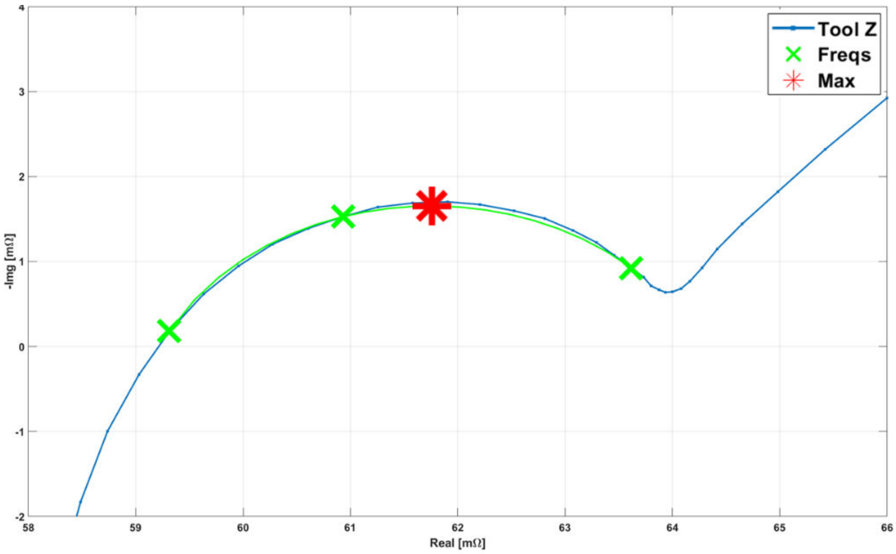
1. Measure battery impedance at three fixed frequencies.
2. Evaluate circle parameters (a, b, c) using a mathematical model.
3. Determine the peak of the second arc.

Figure 10. Circle algorithm



The proposed method showed errors of approximately 43 μΩ (≈0.1%) in experimental setups with 18650 cylindrical batteries, as shown in Figure 11.

Figure 11. Experimental results



The solution is designed to be fast, energy-efficient, and suitable for real-time applications. It can also be generalized in different ways, such as using different optimization algorithms or using neural networks (NN) based on the same measurement points.

A possible generalization of this method could be to use more than three points for the measurements. In this case, the previous system of equations for the impedance values for n points can be generalized as follows:

$$\begin{bmatrix} 2x_1 & 2y_1 & 1 \\ \vdots & & \\ 2x_n & 2y_n & 1 \end{bmatrix} \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} -x_1^2 - y_1^2 \\ \vdots \\ -x_n^2 - y_n^2 \end{bmatrix}$$

Or, grouping coefficients in matrix form:

$$P \cdot \begin{bmatrix} a \\ b \\ c \end{bmatrix} = Q$$

The solution can now be obtained by solving the linear system in matrix form, using the pseudoinverse (specifically the Moore-Penrose pseudoinverse) of the data matrix.

$$\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \left(P^T P\right)^{-1} P^T Q$$

5 Conclusions

The application of electrochemical impedance spectroscopy (EIS) significantly enhances battery management systems (BMS) by offering deeper insights into battery health and performance. This method enables non-invasive and real-time estimation of critical battery parameters, such as state of health (SoH), state of charge (SoC), and internal temperature, which are essential to improve battery safety and longevity.

The proposed EIS-based approach, supported by ST hardware based on L9965x BMS chipset and dedicated software, proves accurate impedance measurements on real battery cells with minimal error.

The strategy of using advanced signal processing algorithms for features extraction, such as peak detection and circle fitting on Nyquist plots, allows to efficiently extract relevant electrochemical features while reducing measurement time and battery stress.

This solution is designed to be fast, energy-efficient, and suitable for real-time applications, with potential extensions including the use of more complex optimization methods or neural networks. Overall, integrating EIS data into BMS offers promising advancements in battery monitoring, safety enhancement, and cost reduction.

6 Reference documents

[1] AN6310.

[2] Q. Zhang, C. G. Huang, H. Li, G. Feng and W. Peng, "Electrochemical Impedance Spectroscopy Based State-of-Health Estimation for Lithium-Ion Battery Considering Temperature and State-of-Charge Effect", link, in IEEE Transactions on Transportation Electrification, vol. 8, no. 4, pp. 4633-4645, Dec. 2022, doi: 10.1109/TTE.2022.3160021.

[3] H.P.G.J. Beelen, L.H.J. Raijmakers, M.C.F. Donkers, P.H.L. Notten, H.J. Bergveld, “A comparison and accuracy analysis of impedance-based temperature estimation methods for Li-ion batteries”, link, in Applied Energy, Volume 175, pp 128-140, 2016, ISSN 0306-2619.

[4] J. P. Schmidt, S. Arnold, A. Loges, D. Werner, T. Wetzel, E. Ivers-Tiffée, “Measurement of the internal cell temperature via impedance: Evaluation and application of a new method”, link, in Journal of Power Sources, Volume 243, pp 110-117, 2013, ISSN 0378-7753.

Revision history

Table 1. **Document revision history**

Date	Revision	Changes
07-Nov-2025	1	Initial release.

Contents

List of figures